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Prevalence and co-occurrence of addictive behaviors among former alternative high school youth: A longitudinal follow-up study

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Background and Aims: Recent work has studied addictions using a matrix measure, which taps multiple addictions through single responses for each type. This is the first longitudinal study using a matrix measure. **Methods:** We investigated the use of this approach among former alternative high school youth (average age = 19.8 years at baseline; longitudinal $n = 538$) at risk for addictions. Lifetime and last 30-day prevalence of one or more of 11 addictions reviewed in other work was the primary focus (i.e., cigarettes, alcohol, hard drugs, shopping, gambling, Internet, love, sex, eating, work, and exercise). These were examined at two time-points one year apart. Latent class and latent transition analyses (LCA and LTA) were conducted in Mplus. **Results:** Prevalence rates were stable across the two time-points. As in the cross-sectional baseline analysis, the 2-class model (addiction class, non-addiction class) fit the data better at follow-up than models with more classes. Item-response or conditional probabilities for each addiction type did not differ between time-points. As a result, the LTA model utilized constrained the conditional probabilities to be equal across the two time-points. In the addiction class, larger conditional probabilities (i.e., 0.40–0.49) were found for love, sex, exercise, and work addictions; medium conditional probabilities (i.e., 0.17–0.27) were found for cigarette, alcohol, other drugs, eating, Internet and shopping addiction; and a small conditional probability (0.06) was found for gambling. **Discussion and Conclusions:** Persons in an addiction class tend to remain in this addiction class over a one-year period.

Keywords: multiple addictions, prevalence, co-occurrence, latent transitions analysis, stability of class membership

INTRODUCTION

A variety of behaviors have come to be considered addictions by researchers and practitioners (Demetrovics & Griffiths, 2012), delineated by common features (e.g., appetitive effects, satiation, preoccupation, loss of control; Sussman & Sussman, 2011). Sussman, Lisha & Griffiths (2011) examined data from 83 studies with sample sizes of at least 500, supplemented by smaller scale studies, pertaining to 11 popularly discussed addictive behaviors over a 12-month period. The addictions examined were to cigarettes, alcohol, hard drugs, shopping, gambling, Internet, love, sex, eating, work, or exercise. They found that the 12-month prevalence of one or more of these 11 addictions among U.S. adults averaged 47% of the population, with a 23% co-occurrence (of two or more addictions). They suggested that addictions are just as likely to be a problem of modern, sedentary lifestyles as of neurobiological vulnerability, and that multiple addictions should be examined.

Several previous empirical studies have examined multiple addictions as a matrix measure (e.g., Alexander & Schweighofer, 1989; Christo et al., 2003; Cook, 1987; Greenberg, Lewis & Dodd, 1999; Haylett, Stephenson & Lefever, 2004; MacLaren & Best, 2010; Najavits, Lung, Froias, Paull & Bailey, 2014; Sussman et al., 2014). With this type of self-report measure, several addictions are tapped, generally with one item per type of addiction, arranged in a matrix format. While an addiction matrix measure does not extensively measure any addiction, this approach is prac-

tical, economical, and may actually tap different addictive behaviors.

Sussman et al. (2014) investigated use of a matrix measure approach among former alternative high school youth (average age = 19.8 years) at risk for addictions. Alternative high school youth, in general, are not able to remain in mainstream education because of an inability to obtain graduation credits in a timely manner due to functional problems (e.g., absenteeism, drug use). “Continuation” high school is the name of the alternative school system in California (U.S.A.). Lifetime and last 30-day prevalence of one or more of 11 addictions reviewed in their other work (Sussman, Lisha & Griffiths, 2011) was the primary focus (i.e., cigarettes, alcohol, hard drugs, shopping, gambling, Internet, love, sex, eating, work, and exercise). Also, the co-occurrence of two or more of these 11 addictive behaviors was investigated. Finally, the latent class structure of these addictions, and their associations with other measures, was examined. They found that ever and last 30-day prevalence of one or more of these addictions was 79.2% and 61.5%,

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respectively. Ever and last 30-day co-occurrence of two or more of these addictions was 61.5% and 37.7%, respectively. Latent Class Analysis suggested two groups: a generally Non-addicted Group (67.2% of the sample) and a “Work Hard, Play Hard”-addicted Group that was particularly invested in addiction to love, sex, exercise, the Internet, and work. Supplementary analyses indicated convergent validity with other types of measures (e.g., compulsive Internet use, risky sexual behavior, rigor of exercise); that the single-response type self-reports may be measuring the addictions they intend to measure.

The present study is among the first longitudinal studies which examines the use of a matrix addiction measure, as a follow-up of the Sussman et al. (2014) study with former continuation high school youth. We studied former continuation high school youth with this measure beginning three years after participating in a drug abuse prevention project (see Sussman, Sun, Rohrbach & Spruijt-Metz, 2012). At the three-year follow-up (the baseline in the current study) and one year later, we examined stability of the prevalence of one or more of these 11 addictions using the same addictions matrix measure. We also examined the co-occurrence of two or more of these addictions among this sample at both time-points.

In addition, we again utilized person-centered latent variable approaches to examine the underlying pattern of addictive behaviors to differentiate groups of youth (Collins & Lanza, 2010). Latent Class Analysis (LCA) is a multivariate approach, which assumes that an underlying categorical latent variable determines one's class membership and yields distinct profiles based on students' responses to a set of items. Latent transition analysis (LTA) is a variation of LCA, which can be used to model the prevalence of latent class membership as well as the transitions in latent class membership over time (Collins & Lanza, 2010).

METHODS

Subjects

Subjects for the analysis were former continuation high school youth in southern California, who had attended any of 24 schools three years prior, as part of a drug abuse prevention program (Sussman et al., 2012). These subjects were followed up one year later to provide a longitudinal perspective. Of 717 subjects measured at the baseline of this study, a total of 538 subjects were followed up and reported complete data for the current analysis (75% follow-up rate). Attrition analysis compared participants at baseline who were lost to follow-up or who were missing complete data and could not be analyzed ($n = 179$) and participants who were followed up and had complete data on key baseline measures, including age, gender, ethnicity, parental education, and the 11 lifetime addiction items from the matrix measure. The only significant difference found was regarding gender (chi-square = 9.4, $df = 1$, $p = .002$). Men were more likely to drop out of the study than women (17% of 359 men at baseline dropped out, 9.2% of 348 women at baseline dropped out).

At baseline for the current analysis, among the longitudinal sample, participants averaged 19.9 years of age ($SD =$

0.85 years), 48.1% were male, 68.1% were Hispanic, 11.8% were non-Hispanic White, 20.1% were Other ethnicity, and approximately 64.2% reported that at least one parent completed high school.

Data collection

Data were collected through three methods: telephone, mailings from the office, and home visits (surveys administered at the home and completed immediately or mailed back to the office). First we attempted to call subjects. For those we reached by telephone, we either completed the survey by telephone or mailed surveys to the home if the subject preferred that method. If we were not able to reach subjects by telephone after multiple attempts, we mailed surveys to the subject's home. We also attempted to reach subjects by traveling to the subject's home. Some subjects completed surveys right away at the home; other subjects preferred holding on to the survey and mailing them back to us. Of the 538 surveys completed at follow-up, 49.4% were completed by telephone, 45.2% were completed via home visits (half of those were completed immediately, half were mailed back within two weeks of the visit), and 5.4% were through mailings sent to the home from the office.

Measures

Addictions. The current study used a multi-response addiction matrix measure. This measure began with categories developed by Cook (1987), followed by feedback provided in pilot sessions with one class of alternative high school youth and two classes of college undergraduates. Subjects endorsed ever and past 30-day addiction categories that applied to them, and could write in additional addictions that they felt they experienced. The final version of the matrix measure included responses reported by at least 10 subjects in the pilot study. After completing the measure, they were asked for feedback regarding wording of the measure's items to assist in enhancing its clarity.

The final measure header is: “Sometimes people have an addiction to a certain drug or other object or activity. An addiction occurs when people experience the following: they do something over and over again to try to feel good, for excitement, or to stop feeling bad; they can't stop doing this thing, even if they wanted to; bad things happen to them or to people they care about because of what they are doing.” Next to the header subjects were asked: “Have you ever been addicted to the following things?” and “Do you feel you are addicted to them now (in the last 30 days)?” Twenty-two response categories of addictions were provided along with a 23rd, which permitted participants to indicate an open-ended response to “Any other addiction? Please identify: _____”

The categories were: cigarette smoking; alcohol drinking; marijuana use; other drugs (such as cocaine, stimulants, hallucinogens, inhalants, XTC, opiates, valium or others); caffeine (coffee, or energy drinks such as Red Bull); eating (way too much food each day, binge eating); gambling; Internet browsing (surfing the web); Facebook, Myspace, twitter, MSN, YM, or other online social networking; texting (cell phone use); online or offline videogames (PS3, Xbox, Wii); online shopping; shopping at stores; love; sex; exercise; work; stealing; religion; self-mutilation (cutting,

skin picking, hair pulling); driving a car; gossip; or any other addiction. For the purposes of the present study, only 11 categories were examined to provide a longitudinal extension to the Sussman et al. (2014) study. As in the previous study, marijuana was combined with the other drugs response category to reflect hard (illicit) drug addiction. Internet browsing and Facebook categories were combined to create an Internet addiction category. The online or offline videogames category was not included in the Internet addiction category because gaming might have been offline. Shopping at stores and online shopping were included to assess shopping addiction.

Demographics. Demographic information was collected on age (in years), gender, ethnicity (coded as Latino/Hispanic, White/Caucasian, or other [African American, American Indian/Native American, mixed or other]), and parental educational status. Parent education was measured across both parents, derived from a 6-level variable ranging from “did not complete 8th grade” to “attended or completed graduate school”, and was coded as to whether at least one of the parents graduated high school or not.

Analysis and results

All descriptive statistics were computed in SAS Version 9.3 (SAS Institute Inc., 2012–2013). In the current longitudinal sample, ever and last 30-day prevalence of one or more of these 11 addictions was 70.5% and 55.2%, respectively, at Time 1. Ever and last 30-day prevalence of one or more of these 11 addictions was 73.1% and 56.7%, respectively, at Time 2. Co-occurrence of two or more addictions, ever and last 30-days was 56.1% and 35.4%, respectively, at Time 1. Co-occurrence of two or more addictions, ever and last 30-days was 54.5% and 37.4%, respectively, at Time 2. The average number of lifetime addictions was 2.29 (SD = 2.11) and 2.26 (SD = 2.12), and the average number of addictions in the past 30 days was 1.40 (SD = 1.62) and 1.43 (SD = 1.70), at Time 1 and Time 2, respectively.

Ever (lifetime) addicted on the 11 addictions in order from highest prevalence to lowest prevalence was: love (33.3% and 29.9% at Times 1 and 2), other drugs (29.7% and 30.1%), exercise (26.2% and 23.8%), sex (24.9% and 23.9%), cigarettes (23.2% and 25.1%), binge eating (22.6% and 21.1%), work (19.4% and 19.6%), shopping (18.0% and 15.8%), Internet (14.5% and 15.8%), alcohol (14.9% and 18.8%), and gambling (3.6% and 4.3%). Last 30-day addiction in order from highest prevalence to lowest prevalence was: love (24.0% and 21.4% at Times 1 and 2), sex (18.4% and 18.6%), exercise (16.9% and 17.5%), work (15.8% and 15.8%), cigarettes (13.4% and 14.8%), binge eating (13.2% and 14.0%), other drugs (13.2% and 13.1%), shopping (10.9% and 9.5%), Internet (10.2% and 11.4%), alcohol (5.8% and 8.4%), and gambling (2.2% and 2.6%). As with the previous study, the prevalence of ever addicted and last 30-day addiction showed a nearly identical pattern across addictions; and other drug addiction was relatively less prevalent among the behaviors for 30-day addiction versus ever addicted.

Chi-square comparisons were run for each of the 11 addiction categories, for both ever and last-30 day addiction at each time-point, comparing general method of data collection (telephone versus paper completion). Of 11 addictions,

six of them revealed significant differences as a function of data collection method ($p < .05$): alcohol (ever and last 30-days; both time-points), Internet (ever and last 30-days; baseline only), shopping (ever; baseline only), love (ever and last 30-days; both time-points), sex (ever and last 30-days; both time-points), and food (last 30-days, follow-up only). In these cases, prevalence reports by telephone were lower than by paper questionnaire. The magnitudes of the differences were on average approximately 15%, across time-points for alcohol, food, shopping, Internet and love; but larger for sex (on average 20% for ever and for last 30-days, across time-points).

Ethics

The study procedures were carried out in accordance with the Declaration of Helsinki. Subjects were informed that their participation was voluntary and that they could withdraw from participation at any time without penalty. Confidentiality of responses was emphasized for all subjects. Questionnaires were identified by number-only on computer. Subjects also were notified that a Certificate of Confidentiality had been achieved to legally protect responses provided. The Institutional Review Board of the University of Southern California-Health Sciences Campus approved the study and reviewed it annually. All subjects were informed about the study and all provided informed consent.

LCA and LTA analysis and results

Latent class and latent transition analyses were conducted in Mplus (Muthén & Muthén, 2004) following procedures recommended by Collins & Lanza (2010). Our analysis focused on determining: (1) whether the latent class model previously established in the cross-sectional analysis replicated in the longitudinal sample; and (2) the probabilities of participants' transitioning from one latent class to another over time (i.e., from T1 to T2). To determine whether the 2-class factor mixture model established in the cross-sectional sample replicated in the longitudinal sample we conducted a series of analysis steps. First, we estimated the 2-class model separately for each time-point and evaluated whether a two-class model fit the data better at T2 compared with models with greater numbers of classes. Next, we estimated the two-class model simultaneously across the two time-points, freely estimating the conditional, item-response probabilities for each addiction type across the time-points. Next, we estimated a model in which the two classes were estimated simultaneously across time-points but the conditional probabilities for each addiction type were constrained to be equal across the two time-points. The latter model was thus nested within the former model in which probabilities were estimated freely across the time-points: the two models were identical except for the constraints placed on the conditional probabilities. If the fit of a nested, more restricted, model is not significantly worse than the fit of the less restricted version of the model, then the simpler, more restricted, model is preferred. In the present case, selection of the nested or constrained model would conclude that the item-response probabilities across the two time-points did not differ and the latent classes represented the same structure at both time-points.

Table 1. Fit statistics for the different models tested

	No. of classes	G^2 (df)	Bayesian Information Criterion (BIC)	Akaike Information Criterion (AIC)	Loglikelihood value (ℓ)	Entropy value
Model 1	2	413.9 (2007)	4100.703	4002.689	−1978.35	0.70
Model 2	2	468.2 (2015)	4144.186	4045.996	−1999.99	0.71
	3	432.0 (2002)	4177.853	4028.434	−1979.22	0.75
	4	382.3 (1989)	4209.912	4009.265	−1957.63	0.72
	5	372.1 (1979)	4247.000	3995.123	−1938.56	0.72
	6	345.8 (1967)	4297.000	3993.894	−1925.95	0.76
Model 3	2	NC	8127.422	7926.068	−3916.03	0.76
Model 4	2	NC	8000.477	7893.374	−3921.68	0.76

Notes: G^2 = likelihood-ratio statistic; df = degrees of freedom; Model 1: Model tested separately for Time 1 (baseline; T1); Model 2: Model tested separately for T2 (follow-up; T2); Model 3: Model tested simultaneously for T1 and T2 with probabilities estimated freely across time-points; Model 4: Model tested simultaneously for T1 and T2 with item-response probabilities constrained to be equal. NC = Not computed because the frequency table for the latent class indicator model part was too large (this is common with models with large df).

Model fit was evaluated based on the likelihood-ratio statistic (G^2), Bayesian Information Criterion (BIC; Schwartz, 1987), Akaike Information Criterion (AIC; Akaike, 1987), loglikelihood value, and entropy values. However, we relied more heavily on AIC and BIC because the relatively large number of observed variables measuring the latent variable rendered the degrees of freedom very large. Large degrees of freedom tend to affect the reference distribution for the G^2 statistic in a way such that G^2 is not well-represented by the chi-square distribution (Collins & Lanza, 2010). In addition to AIC and BIC, the Lo–Mendell–Rubin Test was employed to determine the optimal number of latent classes represented by the data.

The 2-class model fit the data better at T2 than models with more classes. Table 1 (see Model 2) shows the goodness of fit statistics corresponding to a series of LCA models tested for T2. Specifically, models ranging from two to six latent classes were fit. BIC increased as the number of classes increased. Although AIC decreased with the increasing number of classes, the decreases were small. Table 2 shows the results of the Lo–Mendell–Rubin Test. Next, we performed the nested model comparison. Table 1 shows model fit statistics for the free model (Model 3) and the constrained model (Model 4). Since G^2 was not computed because of the large number of degrees of freedom, a nested model comparison using a chi-square difference test was not possible. Instead, we compared BIC and

AIC values between the models. Both BIC and AIC values were lower for the constrained model compared with the free model. Thus, it was concluded that item-response or conditional probabilities for each addiction type did not differ between time-points. As a result, the LTA model constrained conditional probabilities to be equal across the two time-points.

Table 3 shows the results of the LTA. The pattern of latent class prevalence or membership at T1 was similar to the pat-

Table 3. Two-Latent-Status Model of past 30-day addictions across Time 1 and Time 2 ($N = 538$)

	Latent Status	
	Class 1	Class 2
<i>Probability of membership</i>		
Time 1	0.33	0.67
Time 2	0.35	0.65
<i>Conditional probability of a Yes response¹</i>		
Cigarettes	.10	.22
Alcohol	.02	.17
Other drugs	.06	.26
Eating	.06	.27
Gambling	.005	.06
Internet	.04	.24
Shopping	.05	.21
Love	.08	.49
Sex	.05	.44
Exercise	.04	.42
Work	.02	.40
Probability of transitioning to T2 latent status conditional on T1 latent status		
Class 1	0.90	0.10
Class 2	0.14	0.86

Notes: ¹Constrained to be equal across T1 and T2 (assumption is that latent classes are invariant across time).

Table 2. Lo–Mendell–Rubin Adjusted Likelihood Ratio Test (LRT)

No. of classes compared	Value	P -value	Decision
6 vs. 5 ($H_0 = 5$)	24.94	0.26	Accept the null
5 vs. 4 ($H_0 = 4$)	36.61	0.22	Accept the null
4 vs. 3 ($H_0 = 3$)	46.27	0.12	Accept the null
3 vs. 2 ($H_0 = 2$)	43.20	0.07	Accept the null
2 vs. 1 ($H_0 = 1$)	320.4	<0.0001	Reject the null

Notes: Analyses pertain to follow-up data. H_0 = null hypothesis regarding number of classes.

tern at T2. The prevalence of “addiction” latent status (i.e., Class 2) was greater than the prevalence of “non-addiction” (i.e., Class 1) latent status. The item-response probabilities, constrained to be equal across time-points, were similar to item-response probabilities reported in the previous study (Sussman et al., 2014): in the addiction class, larger conditional probabilities (i.e., 0.40–0.49) were found for love, sex, exercise, and work addictions; medium conditional probabilities (i.e., 0.17–0.27) were found for cigarettes, alcohol, other drug use, Internet, eating, and shopping addiction; and a small conditional probability (0.06) was found for gambling. Lastly, we compared transition probabilities between the latent classes. Transition probabilities tell how change occurs between latent classes over time. At the bottom of Table 3, transition probabilities are shown in terms of incidence of transitioning to the column latent class, conditional on earlier membership in the row latent class. The diagonal of the transition probability matrix shows the probability of being in a particular latent class at one time based on being in that same class at the earlier time. In the present case, the diagonal of the transition probability matrix represents the probability of remaining stable in addiction versus non-addiction class over time. Our data indicated that both addiction and non-addiction classes were quite highly stable over time.

DISCUSSION AND CONCLUSIONS

Ever and last 30-day prevalence of these 11 addictions is similar across T1 and T2. The two-class LCA analysis solution was replicated in the LTA analysis. The present study again suggested the existence of a generally non-addicted group as well as an apparently “Work Hard, Play Hard”-addicted group, based on the relative prevalence of the different addictions (see Sussman et al., 2014). Indeed, love, sex, exercise, and work showed the highest prevalence. Also, longitudinally, youth tended to maintain the same latent class they exhibited one year prior. One may speculate that youth did have specific addictions or addiction sets “of choice” that are not exchangeable. Either individual neurobiological differences or stable and individually-different lifestyle contexts could have facilitated such stability in addiction latent class membership. In any case, the addiction matrix items demonstrate a sort of test–retest reliability over a substantial period of time.

Limitations and future research

There are at least three limitations of the present study, in common with the previous cross-sectional study. First, differences in sampling could bias prevalence estimates, although the relative pattern of addiction prevalence and co-occurrence was similar comparing paper versus telephone-completed data. Also, the confidentiality of the protocol used would serve to minimize response bias. Still, one cannot rule out report biases due to sampling.

Second, while the addiction matrix-type measure has been investigated in previous work, much more work on the validation of addiction matrix-type items is needed, along with additional longitudinal studies. Very recently, Konkoly Thege, Woodin, Hodgins & Williams (2015) investigated

the five-year trajectories of exercise, sex, shopping, SNS, videogaming, and eating addictions among a cohort of 4,121 adults from Ontario, Canada. Their results revealed that most participants reported having problematic over-involvement for just one of these behaviors and just in a single time period. That study differed from the current one in that they studied a general population of older adults (mean age at baseline = 46.1 years), used only a one-sentence descriptor to identify addictions (“Are there activities that you engage in where your over-involvement has caused significant problems for you in the past 12 months?”), examined fewer addictions, and studied involvement in specific addictions as opposed to membership in latent addiction classes.

A third limitation with the current study is the lack of information on the deeper meanings of the latent groups uncovered. We had to infer what the groups likely represent.

Future studies might address being addicted to certain behaviors versus others. For example, one might associate being addicted to love, sex, exercise, or work with social images including “romantic” or as examples of “modern living”. These addictions may be considered more acceptable than being addicted to cigarettes, alcohol, and/or other drugs, and the latter addictions may be associated with “rebellious” or “loss of self-control” types of social images. Still, though, it is not clear why some addictions (e.g., love and sex) were higher in prevalence than some others (e.g., shopping, eating), and why gambling addiction was so low in prevalence. One may speculate that the difference in prevalence is in part a function of expenses. Clearly, more research is needed.

Once “locked into” an addiction class membership, youth tend to continue to exhibit membership in that class as opposed to transitioning out of non-engagement or engagement to an addiction. Possibly, the neurobiological effects, social images, or lifestyle features associated with engaging in types of moderate behavior or in specific addictions continue to operate over time, reinforcing the behavior. This longitudinal parameter needs to be understood better. As a first look, we examined specific addictions over time. Over 90% of those not addicted to a specific behavior at the first time-point tended not to be addicted to a specific behavior at the second time-point, except for love addiction (85%) and sex addiction (88%). Thus, there was a stable non-addicted class. We also examined the percentages of those reporting addiction to a specific behavior at baseline who also reported addiction to that same behavior one year later. While LCA indicated a very stable addicted class over time, there was some apparent switching around of classes. The “stability” for specific addictions was fairly high for cigarettes (73%) and hard drugs (56%); more moderate for sex (47%), work (47%), exercise (46%), Internet (43%), love (42%), eating (41%), and shopping (35%); and relatively low for alcohol (28%) and gambling (18%). An examination of such switching is complex and goes well beyond the intended scope of the present paper. However, these data do suggest that more work is needed to understand addiction switching over time (e.g., see Carnes, Murray & Charpentier, 2005).

Finally, and related to the previous point, the present study did not examine specific addiction co-occurrences within or across time. Addiction to specific sets of multiple addictions might be better explored regarding what such

combinations might represent (e.g., alternating cycles of pairs of addictions; Carnes, Murray & Charpentier, 2005).

In summary, the present study contributed to a body of knowledge on prevalence, co-occurrence, latent class structure, and stability of multiple addictions, using an addiction matrix measure, as applied to former continuation high school youth. As with previous studies, the present study highlights the high prevalence and co-occurrence of the addictions among youth and adults. Lifestyle context factors may drive a tendency toward addictions among people, and perhaps severity of addictions might reflect such variables as neurobiology. Possibly instruction in an underlying addiction process that manifests itself in specific behaviors based on lifestyle options may be central to future prevention and treatment efforts. Conversely, the fact that specific addictions show a stable pattern over a one-year period suggests that some tailoring of programming to specific addictions, or sets of addiction, is needed and that, perhaps, ongoing support to maintain change in lifestyle in a healthier direction is needed.

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Authors' contribution: SS took a lead role in the study concept and design, write-up of the manuscript, and he was Principal Investigator of the overall project. PP took a lead role in the data analysis, interpretation of the data, and write-up of the Analysis and Results. PS took the role of senior analyst to assist interpretation of the data and Results write-up. He also was engaged in data management, and he was a co-Principal Investigator of the overall project. LAR and DS-M assisted in making comments on the write-up throughout the manuscript, and they also were co-Principal Investigators of the overall project. All authors had full access to all data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

Conflict of interest: The lead author receives royalty from sales of the prevention program which was mentioned briefly in this manuscript. However, there is no conflict of interest present regarding the current topic or otherwise here.

REFERENCES

- Akaike, H. (1987). Factor analysis and AIC. *Psychometrika*, 52, 317–332.
- Alexander, B. K. & Schweighofer, A. R. F. (1989). The prevalence of addiction among university students. *Psychology of Addictive Behaviors*, 2, 116–123.
- Carnes, P. J., Murray, R. E. & Charpentier, L. (2005). Bargains with chaos: Sex addicts and addiction interaction disorder. *Sexual Addiction & Compulsivity*, 12, 79–120.
- Christo, G., Jones, S. L., Haylett, S., Stephenson, G. M., Lefever, R. M. H. & Lefever, R. (2003). The shorter PROMIS Questionnaire further validation of a tool for simultaneous assessment of multiple addictive behaviours. *Addictive Behaviors*, 28, 225–248.
- Collins, L. M. & Lanza, S. T. (2010). *Latent class and latent transition analysis for the social, behavioral, and health sciences*. New York: Wiley.
- Cook, D. R. (1987). Self-identified addictions and emotional disturbances in a sample of college students. *Psychology of Addictive Behaviors*, 1, 55–61.
- Demetrovics, Z. & Griffiths, M. D. (2012). Behavioral addictions: Past, present and future. *Journal of Behavioral Addictions*, 1, 1–2.
- Greenberg, J. L., Lewis, S. E. & Dodd, D. K. (1999). Overlapping addictions and self-esteem among college men and women. *Addictive Behaviors*, 24, 65–571.
- Haylett, S. A., Stephenson, G. M. & Lefever, R. M. H. (2004). Covariation in addictive behaviors: A study of addictive orientations using the shorter PROMIS Questionnaire. *Addictive Behaviors*, 29, 61–71.
- Konkolý Thege, B., Woodin, E. M., Hodgins, D. C. & Williams, R. J. (2015). Natural course of behavioral addictions: A 5-year longitudinal study. *BMC Psychiatry*, published online 1-22-2015, 14 pages.
- MacLaren, V. V. & Best, L. A. (2010). Multiple addictive behaviors in young adults: Student norms for the Shorter PROMIS Questionnaire. *Addictive Behaviors*, 35, 252–255.
- Muthén, L. K., Muthén, B. O. (2004). *Mplus user's guide*, 3rd ed. Los Angeles, CA: Muthén & Muthén.
- Najavits, L., Lung, J., Froias, A., Paull, N. & Bailey, G. (2014). A study of multiple behavioral addictions in a substance abuse sample. *Substance Use & Misuse*, 49, 479–484.
- SAS Institute Inc. (2012–2013). *SAS/STAT Software version 9.1.3*. Cary, NC: SAS Institute Inc.
- Schwartz, G. (1987). Estimating the dimension of a model. *The Annals of Statistics*, 6, 461–464.
- Sussman, S., Arpawong, T. E., Sun, P., Tsai, J., Roohrbach, L. A. & Spruijt-Metz, D. (2014). Prevalence and co-occurrence of addictive behaviors among former alternative high school youth. *Journal of Behavioral Addictions*, 3, 33–40.
- Sussman, S., Lisha, N. & Griffiths, M. (2011). Prevalence of the addictions: A problem of the majority or the minority? *Evaluation & the Health Professions*, 34, 3–56.
- Sussman, S., Sun, P., Rohrbach, L. & Spruijt-Metz, D. (2012). One-year outcomes of a drug abuse prevention program for older teens and emerging adults: Evaluating a motivational interviewing booster component. *Health Psychology*, 31, 476–485.
- Sussman, S. & Sussman, A. N. (2011). Considering the definition of addiction. *International Journal of Environmental Research and Public Health*, 8, 4025–4038.